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Predicting On-Time Graduation Using the Decision Tree Algorithm with Forward Selection Optimization (Case Study: Computer Engineering Study Program, Faculty of Computer Science, Brawijaya University)

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Abstract. On-time student graduation is a key indicator of academic effectiveness and higher education quality. Timely graduation reflects efficient academic management, while delays may negatively impact institutional performance and accreditation. Graduation delays are influenced by various academic and non-academic factors, making early prediction essential. This study aims to develop an on-time graduation prediction model using the Decision Tree algorithm optimized with the Forward Selection method. The research was conducted in the Computer Engineering Study Program, Faculty of Computer Science, Universitas Brawijaya, using student data from the 2018–2021 cohorts. The dataset includes both academic and non-academic attributes. The modeling process followed the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, and model performance was evaluated using a confusion matrix and balanced accuracy. The results show that the Decision Tree model without feature selection achieved an accuracy of 63%, while the application of Forward Selection improved the accuracy to 83% and balanced accuracy from 69% to 79%. These findings indicate that feature selection plays an important role in improving prediction performance. The proposed model can support academic stakeholders in data-driven decision-making and in designing strategies to improve on-time graduation rates.

Keywords: on-time graduation prediction, decision tree algorithm, forward selection, academic data, non academic data, CRISP-DM

1 Introduction

Timely graduation is one of the important indicators in evaluating the quality of higher education because it reflects the effectiveness of academic management and students' success in completing their studies within the targeted timeframe[1]. In addition to serving as an indicator of institutional quality, the timely graduation rate is also used in the accreditation process of study programs by the National Accreditation Board for Higher Education[2]. Therefore, early identification of students who are at risk of delayed graduation is essential to support academic decision-making and the development of more appropriate intervention strategies[3].

Based on interviews with the Subcoordinator of the Academic and Student Affairs

Subdivision at the Faculty of Computer Science, Universitas Brawijaya, the Computer Engineering Study Program still faces challenges related to students' timely graduation. Although the graduation rate has improved following the implementation of various academic innovations, monitoring the potential for delayed graduation remains necessary to support evaluation processes and enable more proactive academic policy-making.

The development of Educational Data Mining (EDM) has enabled educational institutions to utilize students' academic data to build graduation prediction models. Various classification algorithms have been applied in previous studies, such as Decision Tree, Naive Bayes, and K-Nearest Neighbor to predict academic performance and student graduation outcomes[4]. Decision Tree is one of the most widely used methods because it offers good interpretability and can generate decision rules that are easy for academic stakeholders to understand[5]. However, the performance of classification models may decline when the dataset contains irrelevant attributes or imbalanced class distributions [6].

Several studies have shown that feature selection techniques and class imbalance handling methods can improve the performance of classification models. Forward Selection is used to gradually select the most relevant features, thereby improving the efficiency and predictive performance of the model[6]. In addition, the Synthetic Minority Oversampling Technique (SMOTE) is widely used to address class imbalance by increasing the representation of minority classes in the training data[7], [8], [9]. Although many studies have discussed student graduation prediction, research that combines Decision Tree, Forward Selection, and SMOTE in the context of the Computer Engineering Study Program at the Faculty of Computer Science, Universitas Brawijaya, remains limited. Furthermore, several previous studies focused primarily on accuracy without thoroughly discussing the performance of minority classes, particularly students who are at risk of delayed graduation.

Based on these issues, this study develops a student graduation prediction model using the Decision Tree algorithm combined with Forward Selection and SMOTE. This study also compares the performance of the proposed model with several other classification algorithms, namely Gaussian Naive Bayes, K-Nearest Neighbor, Logistic Regression, and Random Forest. The evaluation is conducted using several performance metrics, including accuracy, precision, recall, F1-score, and balanced accuracy, to obtain a more comprehensive assessment of the model's performance, particularly for the class of students who are potentially at risk of delayed graduation.

2 Method

This study employs a non-implementation approach using an analytical method. The framework applied is CRISP-DM, which consists of several stages, namely business understanding, data understanding, data preparation, modeling, evaluation, and deployment[10], as illustrated in Figure 1.

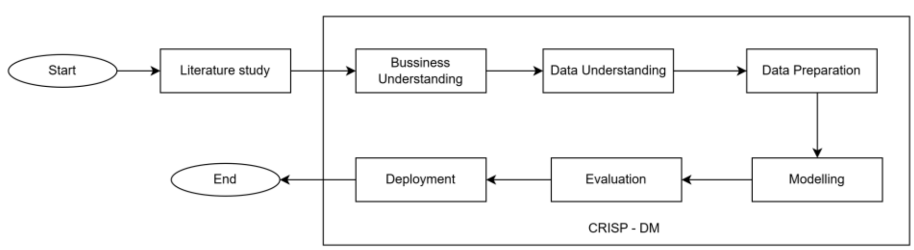

Figure 1. Stages of the CRISP-DM Framework

2.1 Business Understanding

The business understanding stage was conducted to identify the main problem addressed in this study, namely delayed student graduation. On-time graduation is considered one of the important indicators in evaluating the quality of higher education because it reflects the effectiveness of academic processes and institutional performance [4]. In addition, graduation rates are also used as one of the evaluation indicators in higher education accreditation processes [5]. Based on discussions with the academic staff of the Computer Engineering Study Program, Faculty of Computer Science, Universitas Brawijaya, delayed graduation remains an issue that requires continuous monitoring. Therefore, this study aims to develop a classification model to predict student graduation status using a Decision Tree Classifier algorithm combined with Forward Selection and Synthetic Minority Oversampling Technique (SMOTE) to improve classification performance and support academic decision-making. This study focuses on late-stage graduation prediction by utilizing students' academic and non-academic attributes up to the sixth semester.

2.2 Data Understanding

The dataset used in this study consisted of 426 student records from the Computer Engineering Study Program, Faculty of Computer Science, Universitas Brawijaya, from the 2018–2021 cohorts. The target variable was graduation status, which was classified into two categories: on-time graduation and delayed graduation. The number of students who graduated on time reached 322 records, making it the majority class, while the delayed graduation category consisted of 104 records. This distribution indicates that the dataset was imbalanced. The dataset included both academic and non-academic attributes. Academic variables consisted of Semester Grade Point Average (GPA), Semester Credit Units (SKS) from semesters 1–6, inter-semester status, academic leave status, participation in the Merdeka Belajar Kampus Merdeka (MBKM) program, previous school type, and university admission pathway. Non-academic variables included gender, domicile, parents' occupation, parents' education level, and student involvement in Student Activity Units (SKM). The dataset contained both numerical and categorical attributes. Initial analysis was conducted to examine attribute types, class distribution, duplicate data, and missing values before the preprocessing stage.

2.3 Data Preparation

The data preparation stage was conducted to produce a clean and consistent dataset suitable for the classification modeling process. This stage included data transformation, data cleaning, feature encoding, and data splitting. Several categorical variables with a large number of categories, such as parents' occupation and parents' education level, were grouped into more general categories to reduce data complexity and minimize the risk of overfitting. Data cleaning was performed by removing duplicate records and handling missing values. Missing values in numerical attributes were imputed using the median, while categorical attributes were imputed using the most frequent value. Furthermore, categorical attributes were converted into numerical representations using label encoding to enable processing by machine learning algorithms. After preprocessing, the dataset was divided using a stratified train-test split with a ratio of 80:20, resulting in 340 training records and 86 testing records while maintaining the class distribution. To address class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied only to the training data by generating synthetic samples for the minority class based on the similarity between instances. The testing data were excluded from the oversampling process to prevent data leakage and maintain the objectivity of model evaluation.

2.4 Modeling

The modeling stage was conducted by building a classification model using the Decision Tree Classifier algorithm to predict students' graduation status. Before the model training process, feature selection was performed using the Forward Selection method to identify the most relevant attributes for graduation prediction. The selection process was carried out iteratively by adding features based on their contribution to improving model performance. Only features that produced the best evaluation results during the validation process were retained. After obtaining the optimal feature subset, the Decision Tree model was built using the scikit-learn library with the entropy criterion for decision tree construction. In addition to the proposed model, this study also compared the performance of several baseline classification algorithms, namely Gaussian Naive Bayes, K-Nearest Neighbor, Logistic Regression, and Random Forest. Standardization was applied to the K-Nearest Neighbor and Logistic Regression algorithms because both methods are sensitive to differences in data scale.

2.5 Evaluation

The evaluation stage was conducted to assess the performance of the constructed classification model. Model performance was evaluated using a confusion matrix, which is a standard evaluation technique for classification models in educational data mining[11]. Based on the confusion matrix, evaluation metrics such as accuracy, precision, recall, and F1-score and balanced accuracy were calculated to measure prediction performance[5].

2.6 Deployment

The deployment stage involved presenting the research results in the form of a written report and a Streamlit-based dashboard as a visualization medium for classification outcomes. This presentation aimed to make the prediction results easier to understand and to support higher education institutions in academic decision making related to improving on-time student graduation rates.

3 Results and Discussion

3.1 Model Performance Evaluation

This section presents the performance evaluation of the Decision Tree classification model before and after the application of Forward Selection in predicting on-time student graduation. The evaluation was conducted using accuracy, precision, recall, F1-score, macro average, weighted average, and balanced accuracy to provide a more comprehensive assessment of classification performance. The initial experiment was conducted using the Decision Tree model without feature selection to identify the baseline performance and limitations of the model. The classification results are presented in Table 1.

Table 1. Classification Report without Forward Selection

	Precision	Recall	F1-Score	Support
ON_TIME_GRADUATION	0.90	0.57	0.70	65
DELAYED_GRADUATION	0.30	0.81	0.52	21
Accuracy			0.63	86
Macro avg	0.64	0.69	0.61	86
Weighted avg	0.77	0.63	0.65	86
Balanced accuracy			0.69	

Based on Table 1, the Decision Tree model without Forward Selection achieved an accuracy of 63% and a balanced accuracy of 69%. The model showed relatively inconsistent classification performance across classes, as indicated by the macro-average F1-score of 0.61. Although the recall value for the DELAYED_GRADUATION class reached 0.81, the precision value remained low at 0.30, indicating that the model tended to incorrectly classify many students as delayed graduation. These results suggest that the model still experienced limitations in learning relevant patterns when all features were directly used in the classification process.To improve classification performance, Forward Selection was applied to select the most relevant features before the classification process. The classification results after applying Forward Selection are presented in Table 2.

Table 2. Classification Report with Forward Selection

	Precision	Recall	F1-Score	Support
ON_TIME_GRADUATION	0.90	0.86	0.88	65
DELAYED_GRADUATION	0.62	0.71	0.67	21
Accuracy			0.83	86
Macro avg	0.76	0.79	0.77	86
Weighted avg	0.84	0.83	0.83	86
Balanced accuracy			0.79	

Based on Table 2, the application of Forward Selection improved the overall classification performance of the Decision Tree model. The model achieved an accuracy of 83% and a balanced accuracy of 79%, indicating more balanced classification results compared to the model without feature selection. In addition, the macro-average F1-score increased from 0.61 to 0.77, suggesting that the selected features contributed to improving the effectiveness and stability of the classification model. For the DELAYED_GRADUATION class, the model achieved a precision of 0.62, a recall of 0.71, and an F1-score of 0.67. These results indicate that the optimized model was better able to identify delayed graduation patterns while reducing incorrect classifications compared to the model without Forward Selection. This improvement is important because students classified as delayed graduation may require additional academic monitoring and intervention from the study program.

To further evaluate the proposed model, a comparison was conducted with several baseline classification algorithms, including Gaussian Naive Bayes, K-Nearest Neighbor, Logistic Regression, and Random Forest. The comparison results are presented in Table 3.

Table 3. Comparison of Classification Performance Across Models

Model	Accuracy	Macro F1	Weighted F1	Balanced Accuracy
Gaussian Naive Bayes	0.76	0.68	0.76	0.69
K-Nearest Neighbor	0.66	0.62	0.69	0.66
Logistic Regression	0.77	0.69	0.77	0.69
Random Forest	0.79	0.69	0.78	0.68
Proposed Decision Tree + Forward Selection	0.83	0.77	0.83	0.79

Based on Table 3, the proposed Decision Tree model with Forward Selection achieved the best overall performance compared to the baseline classification algorithms, with an accuracy of 83%, macro F1-score of 0.77, weighted F1-score of 0.83, and balanced accuracy of 0.79. Although Random Forest achieved relatively competitive accuracy, its balanced accuracy remained lower than the proposed model. Logistic Regression and Gaussian Naive Bayes showed moderate performance, while K-Nearest Neighbor produced the lowest overall results. These findings indicate that the combination of Decision Tree and Forward Selection was able to improve classification stability and provide more balanced performance across graduation classes while maintaining model interpretability.

3.2 Confusion Matrix

The confusion matrix was used to provide a more detailed illustration of the classification results for each graduation class. Figure 2 presents the confusion matrix of the Decision Tree model without the application of forward selection.

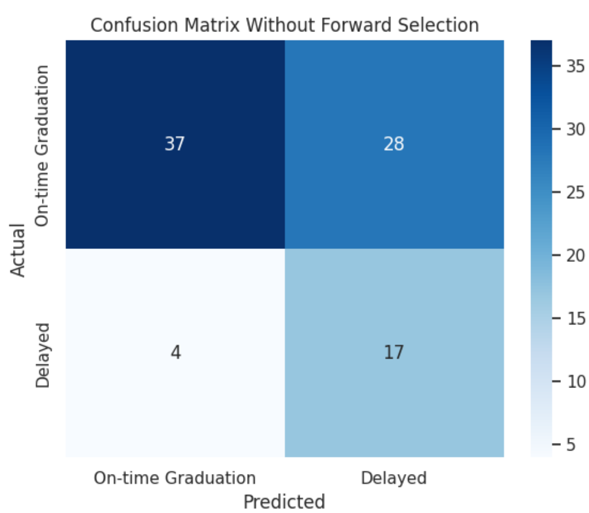

Figure 2. Confusion Matrix without Forward Selection

Based on Figure 2, the model correctly classified 37 students in the On-time Graduation class and 17 students in the Delayed class. However, the model also produced 28 misclassifications in which students from the On-time Graduation class were predicted as Delayed, as well as 4 Delayed instances predicted as On-time Graduation. These results indicate that the model without feature selection still had difficulty in producing balanced classification performance across both classes. Therefore, forward selection was applied to optimize the selected features and improve the classification performance of the model. The confusion matrix of the Decision Tree model with forward selection is presented in Figure 3.

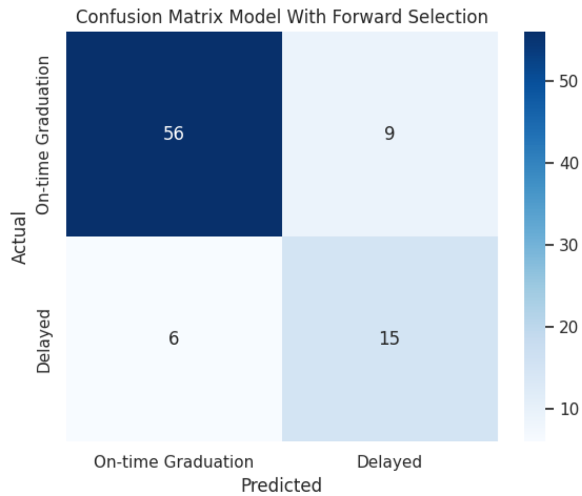

Figure 3. Confusion Matrix with Forward Selection

Based on Figure 3, the application of forward selection improved the classification performance of the model. The model correctly classified 56 students in the On-time Graduation class and 15 students in the Delayed class. Meanwhile, the number of misclassifications decreased to 9 instances for On-time Graduation predicted as Delayed and 6 instances for Delayed predicted as On-time Graduation. These results indicate that the model with forward selection was able to produce more balanced classification results compared to the model without feature selection.

3.3 Feature Importance

Feature importance analysis was conducted on the features selected through the forward selection method to identify which features have the greatest influence on predicting on-time student graduation. This analysis was performed to examine the role of each feature in distinguishing between students who graduate on time and those who graduate late. By identifying the most influential features, the model's prediction results become easier to interpret and can highlight the main factors associated with student graduation. The visualization of the feature importance results is shown in Figure 4.

Based on Figure 4, the MBKM feature has the highest contribution to the on-time student graduation prediction model. This result indicates that MBKM participation was one of the most influential features used by the model in distinguishing between graduation classes. In addition to MBKM, the number of semester credit units in the third semester (SKS_3) and the fifth semester (SKS_5) also showed relatively high contributions to the prediction results. These features may reflect differences in students' academic patterns during their study period.

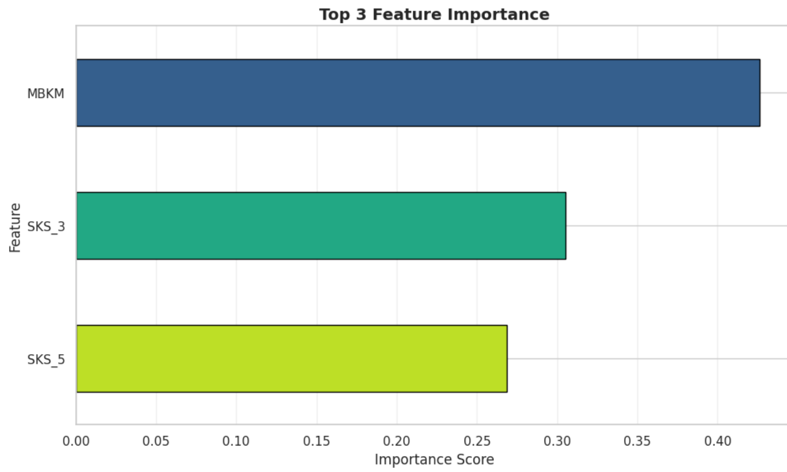

Figure 4. Feature Importance with Forward Selection

The feature importance analysis results indicate that the forward selection method successfully selected the most relevant features while excluding less influential ones. By using only the MBKM, SKS_3, and SKS_5 features, the model produced more interpretable classification results. These findings are also consistent with the decision tree visualization and the extracted decision rules, which identify these three features as the main basis for the student graduation classification process.

3.4 Model Optimization Testing

Model optimization testing was conducted to determine the appropriate parameter configuration for the Decision Tree model in predicting student graduation status. Several parameters were evaluated, including train–test split ratio, maximum depth, minimum samples split, and minimum samples leaf. The parameter selection process was performed using only the training data to avoid data leakage during model evaluation. The final parameter configuration used in this study is presented in Table 4.

Table 4. Final Optimization Parameters

Parameter	Value
Train–Test Split	80:20
Maximum Depth	6
Minimum Samples Split	2
Minimum Samples Leaf	2

Based on the experimental results, the selected parameter configuration produced more stable classification performance across the evaluation metrics. The use of a train–test split ratio of 80:20 provided a balanced proportion between training and testing data, while the maximum depth, minimum samples split, and minimum samples leaf parameters helped control the complexity of the decision tree during the classification process.

3.5 Decision Tree Rules

The decision rules extracted from the decision tree model represent the classification logic in an interpretable form. Each rule corresponds to a path from the root node to a leaf node, describing a specific combination of feature conditions that leads to a predicted class. In this study, the decision rules are constructed based on three main features, namely MBKM, SKS_3, and SKS_5, which are identified as the most influential attributes in determining student graduation outcomes. A total of 29 decision rules were generated; however, only the most representative rules are presented in Table 5 to improve readability and to focus on the dominant classification patterns. The selected rules are based on higher support values and their ability to represent the main decision patterns of the model. The dominant classification pattern is determined by how frequently the rules occur in the dataset and how effectively they distinguish between On-time Graduation and Delayed Graduation.

Table 5. Final Optimization Parameters

Rule	Condition (IF)	Class (THEN)	Support
R1	MBKM ≤ 0.997 ∧ SKS_3 > 19.846 ∧ SKS_5 > 17.5	DELAYED	84
R2	MBKM ≤ 0.997	DELAYED	77
R3	MBKM ≤ 0.997 ∧ SKS_5 > 22.977	ON-TIME GRADUATION	52
R4	MBKM > 0.997 ∧ SKS_5 > 18.0	ON-TIME GRADUATION	48
R5	MBKM > 0.997 ∧ SKS_3 > 22.981 ∧ SKS_5 > 20.5	ON-TIME GRADUATION	19
R6	MBKM > 0.997 ∧ SKS_3 > 23.907 ∧ SKS_5 > 22.5	ON-TIME GRADUATION	30

The decision rules presented in Table 5 indicate that the classification process of the decision tree model is mainly influenced by a combination of MBKM participation and academic performance indicators. Specifically, MBKM, SKS_3, and SKS_5 are identified as the main features used in determining student graduation outcomes. Students with lower MBKM values are more frequently classified as Delayed Graduation, particularly when accompanied by lower or moderate SKS achievements in the early semesters. This pattern shows that limited involvement in MBKM activities is associated with a higher tendency toward delayed graduation. Overall, MBKM plays an important role as part of academic engagement in shaping the decision-making process of the model.

In contrast, students with higher MBKM values are predominantly classified as On-time Graduation, especially when supported by higher SKS_3 and SKS_5 values. The decision rules show that consistent academic performance across semesters is followed by a higher occurrence of On-time Graduation. The combination of active participation in MBKM as part of curriculum-based learning activities and sufficient academic load forms a clear pattern leading to On-time Graduation outcomes. These findings indicate that both academic performance and structured learning engagement contribute to the classification results. Therefore, the extracted rules represent the decision-making behavior of the model in distinguishing between On-time Graduation and Delayed Graduation.

3.6 Implementation Dashboard

The dashboard was designed to help users understand the prediction results through a clear and interactive visual interface. Through this dashboard, users can input student data according to the features used in the model and directly view the on-time graduation prediction results. The dashboard is shown in Figure 5.

Figure 5 presents the student graduation prediction results generated by a web-based system developed using Streamlit. In this interface, the user has input the feature values used in the model, namely the number of credit units in the third and fifth semesters (SKS_3 and SKS_5), as well as the participation status in the MBKM program. After the prediction button is pressed, the system displays the classification result in the form of the student's graduation status, which is ON_TIME_GRADUATION. In addition to the classification result, the system also presents the probability values for each graduation class. These probability values indicate the model's level of confidence in the predicted outcome. This information helps users understand the likelihood of a student being predicted to graduate on time or to graduate late based on the input data, thereby allowing the prediction results to be interpreted more effectively.

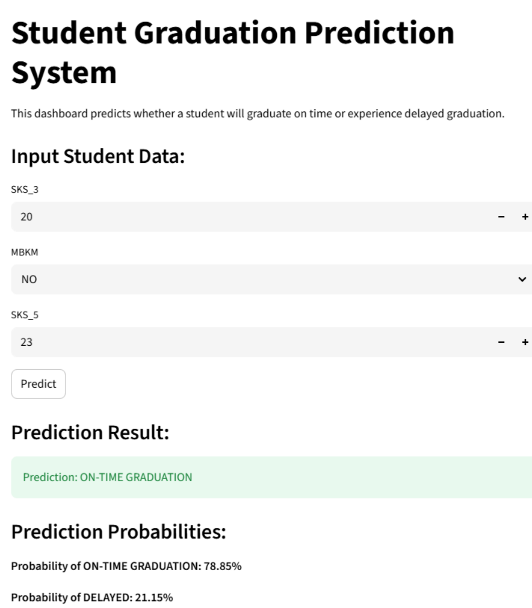

Figure 5. Dashboard Interface

3.7 Discussion

The results show that the application of Forward Selection improved the performance of the Decision Tree model in predicting student graduation status. The optimized model achieved 83% accuracy, with a macro F1-score of 0.77 and balanced accuracy of 0.79, compared to 63% accuracy, 0.61 macro F1-score, and 0.69 balanced accuracy before feature selection. The improvement was also observed in the DELAYED_GRADUATION class, where the F1-score increased from 0.52 to 0.67. In addition, the number of false positive predictions decreased from 28 cases to 9 cases after optimization, indicating that the selected features helped the model produce more balanced classification results for both graduation classes.

Feature importance analysis identified MBKM participation, SKS_3, and SKS_5 as the main features used in the classification process. The dominance of SKS_3 and SKS_5 indicates that academic consistency during the middle semesters contributed strongly to graduation outcomes. Meanwhile, MBKM participation frequently appeared in the generated decision rules, showing that the feature was associated with student graduation patterns within the dataset. In contrast, several non-academic variables were not selected during the Forward Selection process because their contribution to the classification results was relatively lower compared to the selected academic variables.

Compared to the baseline algorithms, the proposed Decision Tree model with Forward Selection achieved the highest overall performance, outperforming Gaussian Naive Bayes, K-Nearest Neighbor, Logistic Regression, and Random Forest. Although Random Forest produced relatively competitive accuracy, the Decision Tree model provides classification rules that are easier to interpret and understand. Therefore, the proposed model may support academic advisors and study programs in identifying students who may require additional academic monitoring related to delayed graduation.

4 Conclusion

This study shows that the application of the Decision Tree classifier with Forward Selection improved the performance of student graduation prediction in the Computer Engineering Study Program, Faculty of Computer Science, Universitas Brawijaya. The optimized model achieved better classification performance compared to the baseline model, with accuracy increasing from 63% to 83%, macro F1-score from 0.61 to 0.77, and balanced accuracy from 0.69 to 0.79. The model also achieved a recall of 0.71 and an F1-score of 0.67 for the DELAYED_GRADUATION class, indicating that the model was able to identify students at risk of delayed graduation more effectively.

The feature selection process identified MBKM participation, SKS_3, and SKS_5 as the main features used in the classification process. These findings indicate that academic progression variables contributed more strongly to graduation prediction compared to the non-academic variables included in the dataset. In addition, the generated decision rules may support academic advisors and study programs in conducting academic monitoring related to delayed graduation. This study was limited to student data from a single study program and institution. Future research may use larger and more diverse datasets or explore alternative feature selection and classification methods to improve prediction performance and model generalizability..

References

1. M. A. S. Pawitra and H.-C. Hung, “Machine Learning Analysis on Students’ Demographic and Performance to Predict On-Time Graduation: A Case Study in Indonesia,” 2024. [Online]. Available: https://www.researchgate.net/publication/379037638
2. BAN-PT, “Pemantauan dan Evaluasi Peringkat Akreditasi,” Jakarta, 2021.
3. Fuad. S, R. Kusumawati, and M. Imamudin, “Comparison of Different Classification Techniques to Predict Student Graduation,” *MATICS : Jurnal Ilmu Komputer dan Teknologi Informasi*, vol. 15, no. 2, Nov. 2023.
4. H. Setiadi, K. Sanjaya, A. Wijayanto, D. W. Wardhani, and H. D. Cahyono, “Comparative Analysis of Classification Algorithms Using Feature Selection Techniques to Predict On-

Time Student Graduation,” *Ingenierie des Systemes d’Information*, vol. 29, no. 4, pp. 1365–1379, Aug. 2024, doi: 10.18280/isi.290412.
5. Gunawan, Hanes, and Catherine, “C4.5, K-Nearest Neighbor, Naïve Bayes and Random Forest Algorithms Comparison to Predict Students’ On Time Graduation,” *Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)*, vol. 4, no. 2, pp. 62–71, 2021, doi: 10.24014/ijaidm.v4i2.10833.
6. B. P. Candra and T. Hidayat, “Optimasi Algoritma C4.5 Menggunakan Metode Forward Selection Dan Stratified Sampling Untuk Prediksi Kelayakan Mahasiswa Penerima Beasiswa,” *Media Online)*, vol. 4, no. 6, pp. 3005–3012, 2024, doi: 10.30865/klik.v4i6.1933.
7. F. Rahman and Mustikasari, “OPTIMALISASI PREDIKSI KELULUSAN MAHASISWA TEPAT WAKTU MENGGUNAKAN BINNING DAN SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE (SMOTE),” vol. 4, no. 1, 2024.
A. Efendi and S. Defit, “Addressing Class Imbalance in Machine Learning for Predicting On-Time Student Graduation at The Islamic University of Riau,” *JURNAL TEKNIK INFORMATIKA*, vol. 18, no. 2, pp. 226–235, Oct. 2025, doi: 10.15408/jti.v18i2.45913.
8. T.-J. Law, C.-Y. Ting, H. Ng, H.-N. Goh, and A. Quek, “Ensemble-SMOTE: Mitigating Class Imbalance in Graduate on Time Detection,” *Journal of Informatics and Web Engineering*, vol. 3, no. 2, pp. 229–250, Jun. 2024, doi: 10.33093/jiwe.2024.3.2.17.
9. P. Chapman *et al.*, “CRISP-DM 1.0 Step-by-step data mining guide,” DaimlerChrysler, 2000.
10. S. Sathyanarayanan and B. Tantri, “Confusion Matrix-Based Performance Evaluation Metrics,” *African Journal of Biomedical Research*, pp. 4023–4031, Nov. 2024, doi: 10.53555/ajbr.v27i4s.4345.